Cognitive stress and learning Economic Order Quantity (EOQ) inventory management: An experimental investigation

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Abstract

We use laboratory experiments to evaluate the effects of cognitive stress on inventory management decisions in a finite horizon Economic Order Quantity (EOQ) model. We manipulate two sources of cognitive stress. First, we vary participants' participation in a competing pin memorization. This exogenously increases cognitive load. Second, we introduce an intervention to reduce cognitive stress by remove participants' abilities to order inventory to only when inventory is depleted. This intervention restricts the policy choice set. Participants complete a sequence of five "annual" inventory management tasks, with monthly ordering decisions. Increases in cognitive load negatively impact earnings with and without the intervention, with the bulk of these impacts occurring in the first year. Participants' choices in all treatments trend to near optimal policy adoption. But only in the intervention and low cognitive load treatment do the majority of choices reach the optimal policy. We estimate the learning dynamics of monthly order decisions using a Markov switching model. Estimates suggest increased cognitive load reduces the probability of switching to more profitable policies, and that in the absence of intervention there is greater policy lock-in. Our results suggests that higher levels of multi-tasking leads to lower initial performance when taking on the inventory management of new product lines, and that the benefits of providing support and task simplicity is greatest when the task is first assigned.

Keywords: Economic Order Quantity, cognitive load, choice set complexity, learning

JEL codes: C92, D83, M11

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1 Introduction

Best inventory management practices call for the solution of dynamic optimization problems. This requires inventory managers to parse complex sets of alternative solutions and to use their short-term memory to hold and process information about the past, present, and future values of key variables. Current workplace trends impose increasing demands upon these managers' cognitive resources (Ruderman et al., 2017). Some examples of these trends are increasing complexity of supply chains (Bode and Wagner, 2015), and widely accepted increasing rates and scale of natural disasters and global social upheavals. We assess how increasing cognitive stress through the introduction of an additional tasks impacts decision-making quality, and how a strategic intervention can mitigate the impact of this stress.

EOQ is one of most commonly used inventory management models, particularly in the wholesale distribution of durable goods. We interviewed inventory managers from four large firms based in either Guangdong or Jiangsu provinces of China. These firms produce goods such as furniture, clothing and household hardware. These managers reported they, and other managers in their respective industries, are typically responsible for managing multiple product lines. They uniformly reported that a major source of performance pressure comes from the common assignment of new product lines. We speculate these pressures tax their cognitive resources as they need to process rates of demand, ordering time frames, holding costs, and et cetera.

The widespread adoption of Economic Resource Planning (ERP) software has partially alleviated this cognitive stress through EOQ expert decision support modules. During our interviews, the managers noted that the ERP system is the predominant tool used to support their multiple product line management. These modules automate the tracking of inventories and sales, as well as recommend order timing and size based upom EOQ solutions. However, they also noted that they retain, and often exercise, the ability to deviate from the system's recommendations. They were most likely to adjust their module inputs or override ordering recommendations during new product launches or fluctuating performance. While this human discretion allows the indirect incorporation of valuable subjective information, associated human biases and judgement errors also create potential inefficiencies.

An extensive literature shows that, even under the best of circumstances, individuals systematically make suboptimal inventory management decisions. Decision-making biases and strategic considerations are often key factors diminishing individual performances in these tasks (Niranjan et al., 2011). When managing the inventory of a perishable good with uncertain demand, i.e. the newsvendor problem, decision makers neither follow the optimal risk neutral or averse policies consistently in experimental studies.[1] When there is a multi-level supply chain for a non-perishable good and certain demand, participants generate large bullwhip effects in beer game experiments. Research have shown key factors driving the excessive inventory levels and variance include strategic uncertainty regarding other decision makers (Croson et al., 2014), limited level two thinking (Narayanan and Moritz, 2015) and failure to fully take account of the future deliveries of past orders. In the setting of a durable good with uncertain demand

[1] See Katok et al. (2011) for an introduction and partial survey of this literature.

optimal inventory management follows the (S, s) policy. Recent experimental studies by (Magnani et al., 2016; Khaw et al., 2017) demonstrate that individuals take time to find the optimal policy, their policy adaptations are idiosyncratic and often participants abandon the optimal policy once found. Despite all being important inventory management environments, none are ideal to begin an evaluation of how cognitive stress diminishes decision-making quality. The reason being decision makers' performances are already suboptimal in their respective most favourable experimental conditions.

A more suitable inventory management environment should have two properties: the optimal policy is invariant to a decision maker's individual preferences and the majority of decision makers can find the optimal policy after repetitions. The finite horizon deterministic EOQ environment potentially possesses these properties. Despite being one of the most commonly used models in operations management, behavioral studies have mostly overlooked it. We choose the parameters of our environment such that the optimal inventory policy of the finite horizon matches that of the infinite horizon; when inventory is depleted, the manager orders an optimal quantity that is the multiple of the monthly demand for the good (Schwarz, 1972). We refer to this multiple as an EOQ cycle length. This EOQ environment has several favourable features for our research question: participants have a relatively good chance of finding the optimal policy; the solution is invariant to a decision maker's risk attitude; and, it is an individual decision problem absent of strategic considerations.

The EOQ solution in our environment is dynamic, as the manager doesn't make the same decision at each point in time. This gives us an opportunity to observe pure learning behaviour in a dynamic problem. In most behavioral supply chain studies, participants do not determine when to act. In our "Unrestricted" treatment, participants can order additional inventory each month regardless of the current inventory level. Our intervention, the "Zero Only" treatment, removes the possibility of violating the optimal inventory policy by forbidding participants from ordering when there is a positive level of inventory. The other aspect of our experimental design is the presence of an additional task competing for the participants' short term memory resources - we call this our "High" treatment. Our "Low" treatment doesn't involve this competing task. The crossing of the intervention treatments and cognitive load treatments constitute our 2×2 experimental design.

There is an a priori belief that our intervention will yield economically significant improvements. A growing and recent literature in economics, e.g., Caplin et al. (2011); Masatlioglu et al. (2012); Abeler and Jäger (2015); Lleras et al. (2017), examines and measures how individual choices are increasingly suboptimal as their choice sets increase in complexity. Our Unrestricted treatment corresponds to the case of an unsupported inventory manager while the simplified choice set of the Zero Only treatment corresponds to active management intervention. This allows our experiment to provide evidence on the value of this practice.

The second factor we investigate is the presence of a concurrent task that competes for the inventory manager's cognitive resources. Tokar et al. (2012) found experimental evidence of cognitive overload with an increased quantity of information. In practice this would involve the introduction of inventory management responsibilities of additional product lines. However, managing the inventory of an additional product line typically introduces cross-demand impacts and potential synergies for inventory costs reductions. To control for the "costs" and "benefits" for successfully inventory management we introduce an additional task unrelated to the inventory management one.

This concurrent task is the memorization of a PIN code at the beginning of each inventory year, and successful recall at the end of the year earns a monetary reward. The PIN task was first introduced by Miller (1956), and has been successively used in economics and psychology to exogenously shock cognitive load. Some recent examples of its application are in food choice (Shiv and Fedorikhin, 1999), generosity (Roch et al., 2000) and intertemporal choice (Hinson et al., 2003). Deck and Jahedi (2015) surveys the use of PIN task in economic experiments with financial incentives as well as reporting new experiments. One of these examines the impact on the ability to solve mathematical problems and finds increasing PIN length reduces individual numeracy. To the best of our knowledge, we are the first to use this technique in behavioral operations management. Correspondingly this allows our experiment to evaluate the impact of asking inventory managers to multi-task.

Our results show that experimental participants earn less when there is a competing task or when the intervention is absent. We observe there is a trend that participants learned to adopt near optimal EOQ policies in general. The restriction of managers to only place orders when inventories are exhausted and the alleviation of the competing task improved the chance for decision makers to reach the optimal inventory policy. It should be noted that these performance differences and suboptimal choices largely occur in the first three iterations of our environment. Our experimental design allows us to test the popular notion that women are better at multi-tasking than men, which we do not find in our inventory management context.

As performance improves rapidly across treatments, we attempt to characterize the individual-level learning driving this trend. We formulate the learning process as a decision tree which permits hierarchies of sophistication. At the first branch we model the propensity to follow the basic characteristics of EOQ solutions: avoiding stock-outs or carrying excess inventories. We find that iterations of the task quickly diminish the probability of making such choices and, surprisingly, imposing high cognitive loads doesn't affect these probabilities. Once participants follow the branch to take EOQ types of actions we model the number of monthly demand orders requested, the EOQ cycle length, using a Markov switching model (Shachat and Zhang, 2017) that is particularly well suited for choice sequences made with low levels of rationality. Our estimates of the model suggest that under high cognitive load participants are less likely to choose EOQ cycle lengths that increase payoffs. The estimates also suggest that with the more complicated policy choice sets of the Unrestricted treatment participants are more reluctant to make large changes in EOQ cycle length leading to greater policy lock-in.

We have found limited other experimental research examining behaviour in EOQ environments. Shachat et al. (2019), building upon the framework we introduce here, examine individual differences in a stationary limited horizon EOQ setting. They find participants with higher cognitive ability tend to choose more effective inventory management policies. However, the performance gap is transitory as participants with lower cognitive ability exhibit faster learning. We found two previous behavioral studies that examine infinite horizon EOQ environments. The EOQ is one of the three environments Stangl and Thonemann (2017) consider in their behavioral study of inventory decision-making under two common alternative frames of performance measurement: inventory turnover and the number of days of inventory held. The former leads managers to over-value inventory reductions relative to the latter. Chen and Wu (2017) examine learning in an infinite EOQ environment in which there is varying inventory ordering and holding costs. The experiment consists of fifty rounds of such inventory decisions. For the first fifteen rounds operational costs were constant, and they varied during the last thirty-five rounds. Their result shows that learning occurs over rounds, and participants learn much faster about the optimal choice under stable environment than under changing environment. Suboptimal decisions tend not to be repeated with deterministic feedbacks. It is important to note that their participants' choice sets are even more restricted than those of our Zero Only treatment. Participants are required to choose from an EOQ restricted choice set whose elements are the number of weeks, their periodicity of demand, of inventory ordered each time inventory is depleted. Thus, their policy choice set consists only of EOQ policies with fixed EOQ cycle lengths. The feedback Chen and Wu (2017) provide participants is the average operational costs generated per week by their EOQ cycle length choice, and participants' reward metrics are the sum of their average weekly performances. While we provide a monthly reported feedback on each decision made, participants experience and collect rewards on a month-to-month basis, which will vary from months when inventory is ordered to those when it is not.

2 Experiment

2.1 Inventory decision task

In the core decision-making part of our experiment, participants complete a series of six discrete dynamic inventory management tasks.[2] We refer to each tasks as a year, indexed zero to five, and each year consists of twelve months, indexed by t. We use the following context to describe these tasks to a participant.

The participant manages the enterprise 'S-store' which sells coffee makers with a constant demand rate (D) of 10 units per month. S-store sells a new model of coffee makers every year. Coffee maker orders are placed prior to the start of a month, an integer amount denoted q_t, and arrive without lag, hence are included in the calculation of a month's opening inventory. The participant chooses the quantity of each monthly order.

Monthly orders and demand determine the changing inventory levels. Let I_t denote the closing inventory for month t. The initial inventory of coffee makers prior to month one is zero, so the first month's opening inventory is the amount of the first month's coffee maker order, i.e. $I_0 + q_1 = q_1$. In general, the opening inventory of coffee makers in month t is $I_{t-1} + q_t$. This inventory is drawn down by the monthly sales, the lesser of the monthly order flow of 10 or the opening inventory (i.e. a stockout). This results in the closing inventory of $I_t =$

[2]We use the same inventory management decision problem as Shachat et al. (2019) but with different values for demand, ordering cost and holding cost.

$I_{t-1} + q_t - \min\{10, I_{t-1} + q_t\}$. When the model life cycle concludes at the end of month 12, any remaining inventory is disposed at no cost nor generates but also generates no revenue. Further, we limit a participant's monthly order by its annual demand, i.e., $q_t \in \{0, 1, 2, \ldots, 120\}$.

A participant's compensation, excluding a fixed show-up fee, is proportional to S-store's profits, which are expressed - as are all further monetary quantities - in experiment currency units (denoted ₱). Each coffee maker sells at a price of ₱7. So revenue in month t is $7 \cdot \min\{10, I_{t-1} + q_t\}$. S-store's cost has two component's: a fixed ordering cost, S, of ₱45 whenever she places a strictly positive order; and a constant per-unit monthly inventory holding cost. The monthly inventory holding costs is calculated by multiplying the average inventory of coffee makers held in t, specifically $\frac{(I_{t-1}+q_t+I_t)}{2}$, and the monthly holding cost, h, of ₱1 per unit. The monthly profit of S-store is the difference between the revenue and costs, and is calculated

$$\pi_t(q_t, I_{t-1}) = \begin{cases} 7 \cdot 10 - S \cdot \mathbb{1}_{q_t > 0} - \frac{I_{t-1}+q_t+I_t}{2} \cdot 1 & \text{if } I_{t-1} + q_t \geq 10 \\ 7 \cdot (I_{t-1} + q_t) - S \cdot \mathbb{1}_{q_t > 0} - \frac{I_{t-1}+q_t}{2} \cdot 1 & \text{if } I_{t-1} + q_t < 10 \end{cases}$$

where, $\mathbb{1}$ is the indicator function.

A participant i's inventory *policy* for year a is the sequence of the twelve monthly quantity orders, $Q_{i,a} = (q_{i,1}, q_{i,2}, \ldots, q_{i,12})$. For a given inventory policy S-store's annual profits are,

$$\Pi_{i,a}(Q_{i,a}) = \sum_{t=1}^{12} \pi_t.$$

In the supply chain literature, the set of EOQ policies is the subset of inventory policies which only place a quantity order once inventory reaches zero with no stockouts allowed. In our dynamic decision making environment, stockouts can occur if a non-optimal policy was chosen previously. Correspondingly we adjust the definition of an EOQ policy to classify choices at these points off the optimal path.

Definition 1. *An EOQ action is a temporal inventory management decision satisfying the following conditions:*

(1). A participant only orders when the closing inventory of the previous period is less than 10 units, i.e., $q_t > 0$ *when* $I_{t-1} < 10$*;*

(2). A participant doesn't order when the closing inventory of the previous period is more than 10 units, i.e., $q_t = 0$ *when* $I_{t-1} \geq 10$*;*

(3). Participant's order guarantees no stockouts in t, i.e., $I_{t-1} + q_t \geq 10$.

Definition 2. *An EOQ policy is a inventory management policy that consists only of EOQ actions.*

The original EOQ model solution is derived assuming an infinite demand horizon, in which the average cost minimizing EOQ policy is to order the following quantity whenever the closing inventory of the previous period is zero,

$$q^* = \sqrt{\frac{2DS}{h}}. \tag{1}$$

In our context then the cost minimizing policy would be to order 30 coffee makers, an EOQ cycle length of three months, whenever closing inventory of the previous period is zero. This would also be the profit maximizing policy as average revenue is constant, up to the monthly demand capacity, and greater than the minimum average cost. In our finite horizon setting the optimal policy does not change. But if an inventory manager deviates from this policy early in the year the optimal course can involve alternative EOQ actions later in the year.

Schwarz (1972) characterizes the optimal EOQ policies for the finite horizon of T months. First, we note the result that average total cost minimizing policy is to order according to Equation 1 if T is an integer multiple of the $\frac{q^*}{D}$. As simply following the EOQ policy of ordering 10 units each period is profitable in our environment, profit maximization will call for satisfying the full annual demand. The EOQ policy of always taking the EOQ action of 30 when inventory is depleted maximizes profit in addition to minimizing average cost.

As individuals can and do fail to act suboptimally we now consider alternative, i.e. shorter in this case, decision horizons. Let $C(T)$ be total incremental cost over the finite time interval T. We restrict our attention to policies which only place orders when inventory is zero. An EOQ cycle length is the interval of months between such orders, denoted by s_k, which is the interval between the $(k-1)th$ and the kth order. Let $C(s_k)$ be the total incremental cost for an EOQ cycle, and n be the number of orders over T. We can formulate the problem as

$$\min C(T) = \sum_{k=1}^{n} C(s_k) \qquad s.t. \quad \sum_{k=1}^{n} s_k = T$$

where

$$C(s_k) = S + hDt^2/2.$$

From the quadratic formulation, it is clear that in the optimal solution all of the s_k are of the same length. An EOQ constant inventory policy, denoted $\bar{Q}^{s_k}$, is one with a constant cycle length.

Let $C^n(T)$ be the total incremental cost for the interval T given n orders,

$$C^n(T) = nS + hDT^2/2n.$$

Minimising $C^n(T)$ gives

$$n^* = \sqrt{\frac{hDT^2}{2S}}.$$

Notice for the first month in our task, i.e. $T = 12$, this yields the same solution as the infinite horizon formulation, $n^* = 4$ and $s_k^* = 3$. Further investigations on situations when the horizon T is sufficiently small reveals that The optimal number of orders, n^*, is the smallest integer satisfying $n(n+1) \geq \frac{hDT^2}{2S}$. With the parameter values in our task, Table 1 gives an overview of the optimal solutions for different values of T.

With our finite horizon of one year, the following set of constant EOQ cycles $s_k = \{1, 2, 3, 4, 6, 12\}$ and the corresponding constant EOQ policies are of particular interest. Table 2 shows for these

Table 1: Optimal solutions for different T in our task

Month	T	$\frac{hDT^2}{2S}$	$n^*(n^*+1)$	The optimal order number (n^*)	The optimal EOQ cycle length (s_k^*) sequence	The optimal order size (q_k^*)
12	1	0.111	2	1	{1}	{10}
11	2	0.444	2	1	{2}	{20}
10	3	1	2	1	{3}	{30}
9	4	1.778	2	1	{4}	{40}
8	5	2.778	6	2	{3, 2}	{30, 20}
7	6	4	6	2	{3, 3}	{30, 30}
6	7	5.444	6	2	{3, 4}	{30, 40}
5	8	7.111	12	3	{3, 3, 2}	{30, 30, 20}
4	9	9	12	3	{3, 3, 3}	{30, 30, 30}
3	10	11.111	12	3	{3, 3, 4}	{30, 30, 40}
2	11	13.444	20	4	{3, 3, 3, 2}	{30, 30, 30, 20}
1	12	16	20	4	{3, 3, 3, 3}	{30, 30, 30, 30}

EOQ constant policies the corresponding annual profits, the number of orders placed annually and the percentage of maximum potential annual profits, i.e. efficiency. Notice that EOQ constant 2 and 4 both generate over 93% of the potential annual profits. Given the minimal loss incurred by adopting these policies we define an alternative decision quality benchmark. When a participant chooses $s_k = \{2, 4\}$ we call this "near optimal" performance.

Table 2: Alternative EOQ constant strategies which do not generate stock-outs or positive closing inventories in month 12 and their respective performance properties.

$\bar{Q}^{s_k}$	The number of orders per year	Constant order size	Profit per EOQ cycle	Annual profit	Efficiency
12	1	120	75	75	15.63%
6	2	60	195	390	81.25%
4	3	40	155	465	96.88%
3	4	30	120	480	100.00%
2	6	20	75	450	93.75%
1	12	10	20	240	50.00%

2.2 Experimental design

Our experimental design has two treatment variables, each of which has two categories. This generates a 2×2 factorial experimental design. We adopt a between subject design, a participant only experiences one of the four possible treatment cells.

The first treatment variable is the feasible set of inventory policies a participant can follow. The first category is called "Unrestricted" where a participant can choose any quantity they wish each month as long as the quantity does not exceed 120. The second category is called "Zero Only", where participants are restricted to ordering only once the inventory level is zero. We expect that the larger set of alternatives in the unrestricted category presents participants with a more difficult learning task.

The second treatment variable is the level of exogenous cognitive load burden we induce by introducing a competing task. In the "Low" cognitive load category participants complete the inventory tasks without distractions. In the "High" cognitive load we introduce an incentivized PIN task that is completed along side the inventory management task and requires the utilization of short term memory. At the start of each year a participant is given 15 seconds to memorise a random 6-digit PIN. The PIN is case sensitive, consisting of numbers, upper and lower case letters.[3] After the completion of the year, a participant is prompted to enter the PIN. Entering the correct PIN unlocks an extra reward of ₽300. A participants only has one attempt at the PIN task. If a participant actively tries to complete the PIN task successfully we expect the diminished access to short term memory to reduce decision making quality and the speed of any learning.

Table 3 summarizes our experimental design and provides summary statistics on the demographics of the participants. We designate treatment cells by the word pairs x-y, where x is feasible set of policies category and y is category of the cognitive load.

Table 3: Summary of the demographic information of participants for each treatment

Treatment cell	Participants	Average age	Male	Postgrad	STEM subjects[1]	Average math level[2]
Unrestricted-Low	41	25	34%	49%	37%	3.68
Unrestricted-High	41	25	37%	44%	56%	3.20
Zero Only-Low	39	25	23%	47%	34%	3.26
Zero Only-High	36	28	50%	56%	28%	3.53

[1] STEM subjects include Engineering & Technology, Life Sciences & Medicine and Natural Sciences. Non-STEM subjects include Arts & Humanities and Social Sciences & Management.
[2] Math Level was self-assessed, and was categorised into 6 levels. 1 = "Below GCSE", 2 = "GCSE", 3 = "A Level", 4 = "Undergraduate", 5 = "Postgraduate", 6 = "Above Postgraduate". Note that GCSE (General Certificate of Secondary Education) is an academic qualification in a specific subject typically taken by school students aged 14-16 of the UK (except Scotland), at a level below A level.

2.3 Experimental procedures

Seven sessions were conducted at Newcastle University Business School experimental economics laboratory during May and July 2017. 162 participants[4] were recruited via random selection for invitation from a participant pool database of the Behavioural Economics Northeast Cluster. All participants were students from Newcastle University except for three who were from Northumbria University.

[3]The PIN is the same for all particpants across each year to ensure control.

[4] We excluded five participants from our data analysis and the participant counts given in Table 3. One participant, in the Zero Only-Low treatment, always submitted the random slider starting position when inventory reached zero. Two other participants, in the Zero Only-High treatment, grossly took advantage of the limited liability rule. The final two excluded participants attended the last session and demonstrated behaviour that they had been briefed about the content of the experiment; they clicked through the instructions without reading them and subsequently provided the solution $\bar{Q}^3$ for all years - even though this was not optimal for the practice year.

Each session lasted no more than sixty minutes, with strict procedures to limit the access to any aides that would provide assistance in calculations or remembering PIN codes. Participants were signed in individually and instructed to leave their personal belongings, including any writing instruments, in the reception area before being escorted to a computer desk placed in a privacy carrel. Each participant was then provided with a pen and two copies of an informed consent document, which they read and signed if they wished to continue their participation. The pen and signed forms were then collected by a monitor. After which participants were sternly informed that no electronic devices - such as mobile phones, calculator, smart watches, etc. - could be used until their session was completed. They were further instructed that the rest of the experimental tasks were fully computerized and they would complete the rest of the experiment only using their mouse. Prior to participants entering the laboratory, all computer keyboards were concealed under a thick opaque cover. This was to done to diminish any access to mnemonic devices for remembering PIN codes. These measures were taken in all sessions to provide control between High and Low cognitive load treatments.

The experiment itself was conducted using a self-contained program developed in oTree (Chen et al., 2016). Access was restricted to other programs on the computer. The sum of these measures eliminated many of the tools participants commonly used to perform mathematical calculations. This dismal work environment was applied to all four treatment cells.

Once instructed to start by the monitor, participants read through the instructions[5] at their own pace. After reading the instructions, participants were asked to complete seven multiple choice questions designed to ensure that they understand the calculation of costs and profits. Participants who provided more than two incorrect answers had to review the mistaken questions with one of the experimenters before proceeding to the decision tasks.

Participants then participated in the six year decision task sequence, followed by a short post-experiment survey which collected demographic information. Year 0 was a practice round which used an alternative set of cost parameters[6] from those of Years 1 through 5, and the performance in this task did not affect a participant's total earnings. The purpose of the practice year was to help familiarize the participants with the task and the decision screen. Orders were entered by moving a slider whose value range was zero to one hundred and twenty. The initial point of the slider was random each month, and in the case of an Zero Only treatment with a positive starting inventory it was greyed out. The decision screen included a table providing the entire history of a participant's monthly ordering choices, as well as opening inventory, units sold, closing inventory, sales revenue, ordering costs, holding costs and profits.[7] For participants who experienced the High cognitive load treatment, we provided an opportunity to practice the PIN task in the practice Year.

Participants then completed the Years 1 through 5 decision tasks. Participants were paid for their accumulated earnings from these decision tasks, at the conversion rate of ₱300 = £1, as well as a £5 show-up fee. There was limited liability; to ensure the motivation to make profits

[5] In the first Appendix, we provide a complete set of instructions.
[6] In the practice year the order costs were ₱45 and the holding costs were ₱0.5.
[7] We provide screen captures of these interfaces in the Appendices.

would not be affected by a large negative earnings made in a particular year, any negative profits made in a year will be treated as 0 earnings.[8] The average earnings across all treatments were £13.37 per participant, including the participation fee.[9]

One last important aspect of the experiment was the fixed length of time a participant had to complete the inventory management task for a year. We required that a participant spend exactly four minutes completing each task in Years 1 through 5. This was designed to prevent participants from racing through the monthly decisions in order to reduce the cognitive cost of remembering their PIN. If a participant completed their twelve monthly decisions early they could not advance to the next period (or enter the PIN) until the four minutes expired. If they failed to complete the twelve tasks before the time expired, the computer program executed the remaining months sales with the existing inventory stock.

3 Empirical evaluation of treatment effects

We evaluate the treatment effects of restricted inventory policy choice sets and increased cognitive load by considering their impacts upon participant's earnings in the inventory management tasks, the propensity to choose optimal inventory policies, and then the efficacy of the PIN task and whether performance in that task is correlated with inventory performance.

3.1 Hypotheses

Our motivation of treatment variables leads to several natural hypotheses. Naturally, better performance leads to greater average annual earnings and is indicated by greater percentage of participants adopting optimal (near-optimal) inventories. Increases in cognitive load reduces short term memory capacity and lead to diminished performance in both the Zero Only and Unrestricted policy choice sets, giving the following hypotheses:

Hypothesis 1.a. *Participants perform better in the Zero Only-Low treatment than the Zero Only-High treatment. This will be reflected in two measures: average annual earnings and the percentage of participants who adopt optimal (near-optimal) inventories.*

Hypothesis 1.b. *Participants perform better in the Unrestricted-Low treatment than the Unrestricted-High treatment. This will be reflected in two measures: average annual earnings and the percentage of participants who adopt optimal (near-optimal) inventories.*

The set of inventory policies in the unrestricted is much larger than and only adds suboptimal alternatives to the EOQ restricted set of policy choices. The reducing the focalness of EOQ strategies and greatly complicating participants' choice sets in the Unrestricted treatments leads to our next set of hypotheses:

Hypothesis 2.a. *Participants perform better in the Zero Only-Low treatment than the Unrestricted-Low treatment. This will be reflected in two measures: average annual earnings and the percentage of participants who adopt optimal (near-optimal) inventories.*

[8] This limited liability only affected the earnings of five participants in five different years.

[9] The average earnings of Low treatment (without PIN task) was £11.58 per participant, while the average earnings of High treatment (with PIN task) was £15.23 per participant.

Hypothesis 2.b. *Participants perform better in the Zero Only-High treatment than the Unrestricted-High treatment. This will be reflected in two measures: average annual earnings and the percentage of participants who adopt optimal (near-optimal) inventories.*

In our treatments that involve the PIN task, participants need to memorize the PIN as well as making monthly ordering decisions. Buser and Peter (2012) define multitasking as switching back and forth between two ongoing tasks, which can be applied in treatments with the PIN task. Popular best-selling books[10] advertise the stereotype that women are better at multitasking. However, experimental results from Buser and Peter (2012) do not support such stereotype. Our experiment is an opportunity to evaluate the women are better at multi-tasking conjecture in an inventory management context.
Hypothesis 3. *In treatments involving increased cognitive load, i.e., both Zero Only-High and Unrestricted-High treatment, women perform better than men.*

3.2 Annual inventory profits

We test the differences in average annual profit for different treatment groups using two-sided t-tests and non-parametric Wilcoxon rank-sum tests. As participants have the best performance with the intervention and without the cognitive load, we use Zero Only-Low treatment as a reference point to demonstrate profit loss resulting from the presence of more complicated choice sets and a shock to their cognitive load. We report the results of these hypotheses tests in Table 4. The first two rows indicate that both the absence of the intervention and shocking their cognitive load each negatively impact average annual profits both statistically and economically. More complicated policy choices cause more profit loss than High cognitive load.

When we examine the effect of exogenously increasing a participant's cognitive load conditional on the policy choice set we find mixed support for Hypothesis 1. There is a statistically significant reduction in average in earnings in the Zero Only treatment, but not in the Unrestricted treatment. We do find stronger evidence in support of Hypothesis 2, as we find limiting participant's choices to EOQ restricted policies does lead to statistically greater average earnings in both Low and High cognitive load settings.

A disaggregated view of the average annual profits permit insights into learning over time and how our treatments impact it. Figure 1 presents these time trends for each of the four treatments. There are several prominent features of this figure which provide refined insights into our hypotheses results on the average profit levels. First, performance gains are mostly achieved in Years 1 through 3. Second, average earnings are around 90% of the possible earnings in the last two years; except for the Unrestricted-High treatment which are around 5-10% lower. Third, High cognitive load and Unrestricted policy choice sets both cause the greatest negative performance impact in Year 1.

We quantify and assess these remarks by conducting a series of dummy variable linear regressions using random effects estimators and cluster standard errors at the level of the individuals.

[10] See for example Pease and Pease (2001) and its adaptation, Why Men Can Only Do One Thing at a Time and Women Never Stop Talking (Pease and Pease, 2003).

Table 4: Average annual profits by treatment and hypotheses tests for differences in average annual earnings

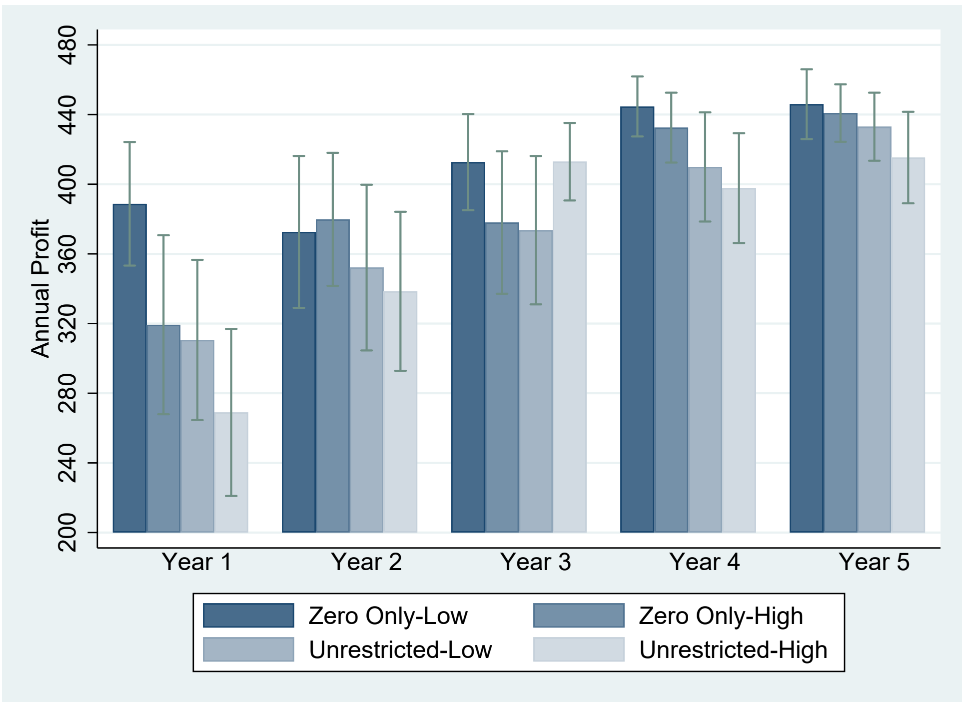
Panel A: Annual profits by treatment

	Unrestricted-Low	Unrestricted-High	Zero Only-Low	Zero Only-High
Average	375.85	366.70	412.94	390.10
Stand. Dev.	129.38	126.87	97.35	113.78

Panel B: Hypotheses tests for differences in average annual profits (p-values reported)

Treatment Comparison	Difference	Profit loss (%)	Two-sided t-tests	Wilcoxon rank-sum
Zero Only vs Unrestricted	30.71	7.64%	0.000	0.001
Low vs High	16.29	4.14%	0.055	0.003
Zero Only-Low vs Zero Only-High	22.84	5.53%	0.038	0.012
Unrestricted-Low vs Unrestricted-High	9.15	2.43%	0.470	0.124
Zero Only-Low vs Unrestricted-Low	37.09	8.98%	0.001	0.012
Zero Only-High vs Unrestricted-High	23.40	6.00%	0.059	0.052

Figure 1: Annual Profits over individual Years and by treatment: Averages and 95% confidence intervals



We report these results in Table 5. In model (1), we simply regress annual profit on a constant and dummy variables for Years 1 through 4, rendering Year 5 the base level. In model (2) we introduce dummy variables for the Zero Only and High treatment categories. In this case the constant reflects the average profit level for Year 5 in the Unrestricted-Low treatment; and the Year 1 through 4 dummy variable coefficients reflect the average annual profits across participants in the Unrestricted-Low treatment. In model (3), we add interaction dummy variables for the Zero Only and High treatment categories to examine if their joint imposition leads to super- or sub-additive impact on annual profit. In model (4), we add individual characteristic dummy variables to exam individual differences.

Table 5: Dummy variable regressions for annual profit: random effects panel data (n=785)

	(1) Annual Profit	(2) Annual Profit	(3) Annual Profit	(4) Annual Profit
Year 1	-112.27***	-112.80***	-122.44***	-122.44***
	(11.24)	(18.34)	(20.77)	(20.83)
Zero Only*Year 1		45.45**	65.22**	63.91**
		(21.97)	(26.77)	(27.09)
High*Year 1		-43.20*	-23.91	-23.91
		(22.17)	(32.23)	(32.32)
Zero Only*High*Year 1			-40.40	-39.09
			(44.19)	(44.46)
Year 2	-73.39***	-82.86***	-80.89***	-80.89***
	(10.02)	(19.08)	(22.92)	(22.98)
Zero Only*Year 2		11.56	7.53	5.07
		(20.05)	(29.81)	(30.10)
High*Year 2		8.04	4.11	4.11
		(20.13)	(29.94)	(30.02)
Zero Only*High*Year 2			8.24	10.69
			(40.13)	(40.40)
Year 3	-38.81***	-38.75**	-59.41***	-59.41***
	(7.78)	(15.39)	(18.34)	(18.39)
Zero Only*Year 3		-16.24	26.15	28.35
		(15.78)	(22.69)	(22.85)
High*Year 3		15.70	57.02***	57.02***
		(15.65)	(19.90)	(19.95)
Zero Only*High*Year 3			-86.59***	-88.79***
			(30.82)	(30.97)
Year 4	-12.85***	-20.08**	-23.09**	-23.09**
	(4.61)	(9.40)	(11.57)	(11.61)
Zero Only*Year 4		15.59*	21.75*	21.90*
		(9.03)	(12.16)	(12.23)
High*Year 4		-0.45	5.56	5.56
		(9.25)	(15.57)	(15.62)
Zero Only*High*Year 4			-12.59	-12.74
			(18.12)	(18.19)
Zero Only		19.12*	12.96	14.30
		(10.31)	(13.87)	(15.17)
High		-11.70	-17.71	-22.49
		(10.45)	(16.25)	(16.77)
Zero Only*High			12.58	15.31
			(20.71)	(22.68)
Male				15.04
				(11.85)
Postgrad				-14.88
				(12.03)
STEM				12.18
				(11.47)
Math Level				-2.69
				(5.13)
Constant	433.40***	430.01***	433.01***	440.60***
	(5.28)	(8.56)	(9.70)	(20.84)
Wald χ^2	183.28	210.84	228.77	239.23

Standard errors in parentheses adjusted for clusters in individuals
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our treatment effects for Zero Only and High are largely generated by their Year 1 impacts as seen by their individually significant coefficients in models (2) and (3). We conduct a Chow test, for which the null is model (1) versus the alternative of model (2), i.e. the joint differences of the two treatments are significant. The resulting χ^2-stat is 27.32, and has a p-value of 0.002. We conduct a second Chow test to compare the veracity of model (3) versus model (2). The resulting χ^2-stat in this case is 8.73, and has a p-value of 0.120.

Our analyses of annual profits leads us to our first set of results.

Result 1. *Reducing the participants' policy choice sets to EOQ restricted ones leads to higher profits. However, these gains predominantly occur in Year 1 - when the participants face the inventory decision problem for the first time.*

Result 2. *Exogenously increasing participants' cognitive load leads to lower profits. However, these losses predominantly occur in Year 1 - when the participants face the inventory decision problem for the first time.*

Result 3. *There is no super- or sub-additive effect of simultaneously exposing participants to the Zero Only and High treatment categories.*

Finally let's consider the differences in average annual profit between male and female participants in treatments involving the PIN tasks. Among the participants who needed to memorize the PINs as well as making monthly ordering decisions, the average annual profits of female and male are 362.95 and 397.22 respectively. Surprisingly, women are not better at multitasking as stereotype suggests. This difference of 34.26 is statistically significant according to both a t-test (p-value $= 0.006$) and a Mann-Whitney test (p-value $= 0.000$), which leads to our next result.

Result 4. *When there are two ongoing tasks, women performs worse than men in terms of profits.*

3.3 Inventory management policy choices

We turn our analysis towards the inventory policy choices of participants. For each participant we evaluate each of the annual inventory policies, $Q_{i,a}$, for whether it is optimal, $\bar{Q}^3$, or if its near-optimal, and EOQ constant strategy of either $\bar{Q}^2$ or $\bar{Q}^4$. Figure 2 depicts the evolution across years of the percentages of participants following optimal and near-optimal policies in each treatment. Inspection of this figure reveals our next set of results.

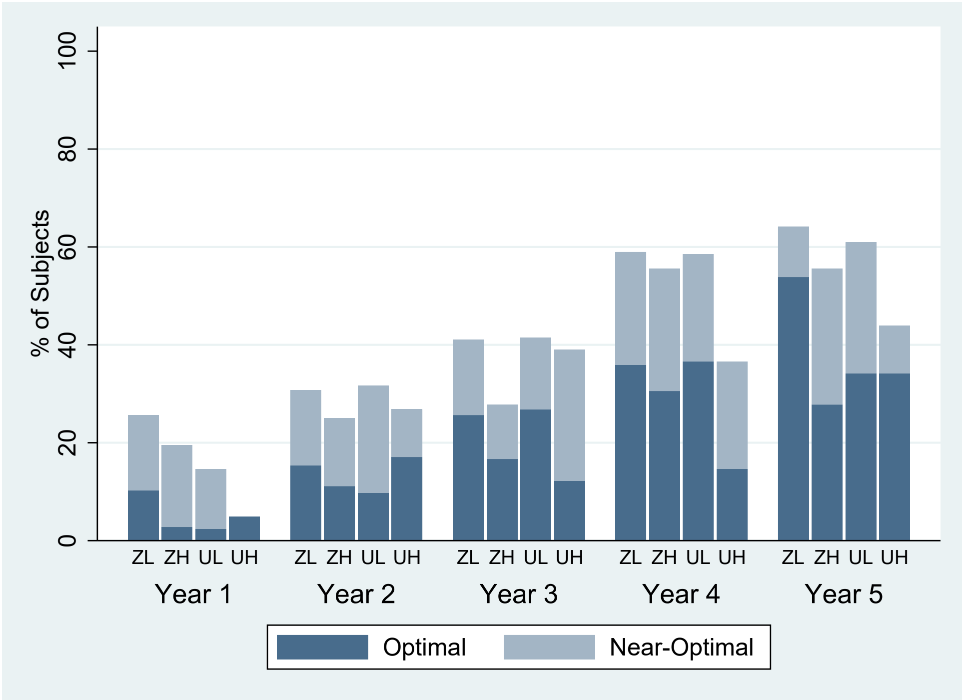
Result 5. *There is a trend in all treatments for increasing use of optimal and near-optimal policies from Year 1 to Year 4.*

Result 6. *High cognitive loads leads to lower percentage use of these policies for both Zero Only and Unrestricted in all five Years.*

3.4 Efficacy of the PIN reward procedure

Next we evaluate the efficacy of procedure for exogenously increasing the cognitive load. Our experimental design faces a challenging balancing act. If the PIN reward procedure is too simple participants will always collect the reward utilizing minimal short run memory resources, and if it is too difficult they could either decide to forgo the mental costs of trying to commit the PIN to short term memory or forgo effort in the Inventory management tasks. A second concern is that raw intelligence is an omitted variable in our analysis which would manifest itself in

Figure 2: Stacked graph of the percentage of participants following optimal and near-optimal EOQ constant strategies: by Year and treatment



a strong positive correlation between a participant's performances in the PIN reward and the Inventory management task.

We provide visual evidence that our design successfully addresses this balancing act in Figure 3. First, we observe that only three out of the seventy-seven participants earned one or less PIN rewards; and at the same time thirty-three out of seventy-seven collected all five pin rewards. Second, there doesn't appear to be a clustering of poor Inventory management performers, below the *ad hoc* threshold of ₱1500, on high or low numbers of earned PIN rewards. Third, there is little evident differences in the conditional means of total profits - suggesting the PIN and inventory management tasks performance are independent.

We quantify the evidence of the independence of PIN and Inventory management task performance by statistically measuring their correlation and testing its statistical significance. Table 6 reports these correlations and the p-values of the hypotheses tests that the correlation is zero. The left portion of the table addresses the correlation between the success of a PIN reward task and the corresponding annual inventory profit. The evidence is mixed. We don't find correlations significantly different from zero in four out of five years, but do find a highly significant positive correlation when we pool all of the years. This analysis suggests potential positive correlation between a correct PIN tasks and individual reward; however this analysis does not allowing for differences in participants' performances for the PIN task. To address this concern we evaluate the correlations between the total number of PIN rewards earned by a participant j and both j's annual profits and her total Inventory tasks profit. We report these correlations in the right side of Table 6. In this analysis we find evidence in favor of no correlation. None of these correlations is significant.

Figure 3: Participants' total inventory management task profits conditional on the number of PIN rewards earned and the corresponding whisker plots for the 50, 75, and 95% quantiles. The numbers across the top are the counts of participants who earned the corresponding number of PIN rewards.

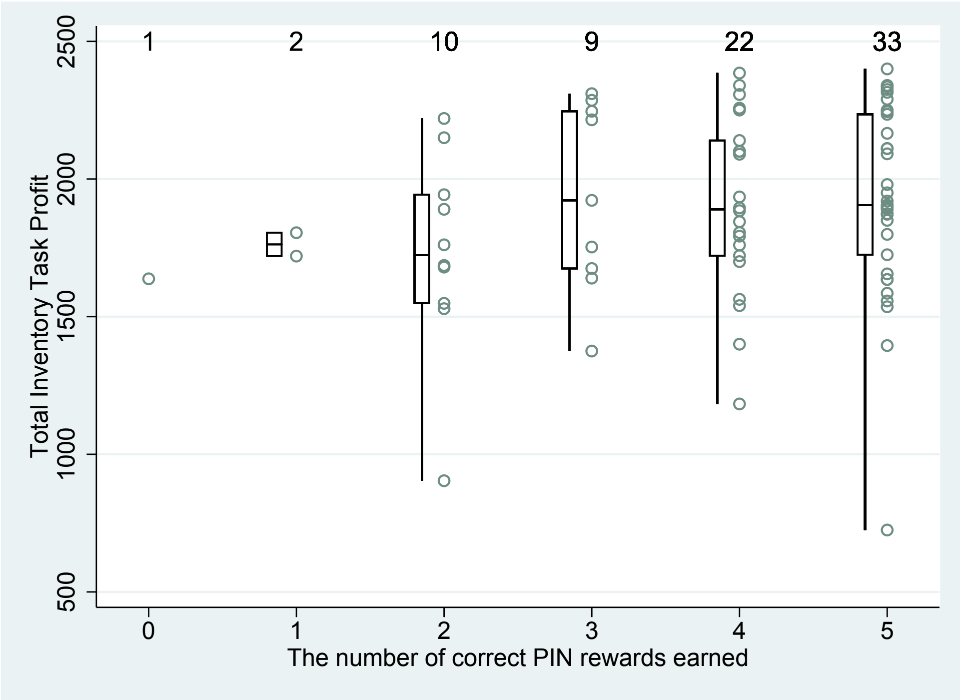


Table 6: Spearman correlations between PIN reward earned in Year a by participant j and j's corresponding Inventory task profit; Spearman and Pearson Rank correlations between a participant j's total number of earned PIN rewards and their Inventory task profits

		PIN reward eared in Year a	Number of PIN reward earned	
		Spearman Rank Corr.	Pearson Corr.	Spearman Rank Corr.
Annual Profit	Year 1	0.08 (0.512)	0.13 (0.248)	0.11 (0.324)
	Year 2	0.12 (0.315)	0.08 (0.507)	0.11 (0.338)
	Year 3	0.21 (0.072)	0.10 (0.391)	0.04 (0.750)
	Year 4	0.09 (0.459)	0.15 (0.182)	0.04 (0.725)
	Year 5	0.14 (0.226)	0.10 (0.379)	0.14 (0.218)
	All Years	0.18 (0.001)	N/A N/A	N/A N/A
Total Profit		N/A N/A	0.179 (0.120)	0.182 (0.114)

1. The p-values of the respective tests are reported in the parenthesis.
2. We don't report the correlations for Total Profit in column three because the calculation will include multiple repetitions of a participant's total inventory profit.
3. We don't report the correlations for all Years in columns for and five because the calculation will include multiple repetitions of a participant's total number of PIN rewards.

4 Learning Dynamics

Rapid behavioural adjustment during the first three annual iterations of our task is one of the most striking features of our data. What is the process of this individual learning? How do the two external sources of cognitive stress impact this process? These are two questions we next attempt to answer. In the management science and behavioural economics literatures, a common approach to model this type of learning often flies under the flag of Experienced Weighted Attraction (EWA) learning (Camerer and Ho, 1999). This approach often considers a blend of simple reinforcement and adaptive payoff expectation valuations for each alternative strategy, and then for the individual to choose the alternatives according to a probability function that puts a higher probability of choice on higher "scoring" alternatives (Amaldoss and Jain, 2010; Kalkanci et al., 2011; Kalkancı et al., 2014; Brandts et al., 2016; Feng and Zhang, 2017). These scores are then updated over time based on counterfactual payoffs and previous decisions.

There are several reasons why a framework such as EWA learning model is a poor fit for our tasks. First, and most importantly, our choice is the amount of demand to order and which has a prominent monotonicity in the number of months. However, the payoff consequences for inventory orders is <u>not</u> monotonic in the number of months. As the information for participants to calculate and maximise the scores of the alternatives are available to them, it seems that the two external sources of cognitive stress impact the learning process in a way of preventing participants from making the calculation and arriving inertia of the optimal choice. A natural way for participants to adjust their orders in is to explore how their performance responds to increases or decreases from previous orders. However, this will inevitably lead to violations of the higher score implies higher probability of choice paradigm of EWA-like learning models. A second problem is the relative low number of actual positive EOQ quantities a participant has an opportunity to make. These makes the estimates of initial scores of the alternatives overly influential on the estimation of the parameters of interest hence the process of learning was not properly reflected.[11] In response to the issues we turn to an alternative learning model introduced by Shachat and Zhang (2017), which accommodates the potential conflict of a natural ordering of the choice set not having monotonicity in value, allows for minimal individual rationality, and successfully works when there are a relatively low number of decisions.

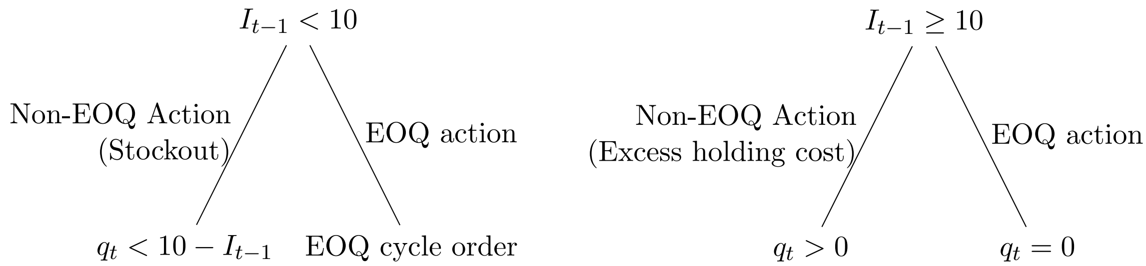
In our final analysis we present and estimate a Markovian learning model for participants' monthly order choices. Generally avoiding *stockout*[12] - thus not foregoing potential profit - and only ordering when sales have exhausted inventory - thus avoiding *excess holding costs* - are two key logical motivations for choosing EOQ consistent actions. We formulate a learning

[11] We have estimated, or attempted to in some cases, various reinforcement learning model (Erev and Roth, 1998) and experienced-weighted attraction learning models (Camerer and Ho, 1999) with logistic linkin functions. We have not reported these results because estimates of the variance term in the link function reversed the higher score - high probability of choice ranking, locked into extreme initial attraction levels, or failed to converge.

[12] We recognise that with our setting, especially in later months, it may be more profitable to suffer a stockout when the open inventory is not too far short from the demand. For instance, in month 9 the optimal dynamic solution is to order 40. However, if open inventory is above 6 units in month 9, it would be more profitable to suffer a stockout and wait until period 10 to order 30. This may lead to a situation in Unrestricted treatment, in which participant deliberately wait out a stockout. However, out of 4920 observations from Unrestricted treatment, such situation never occurred.

process for monthly choices as a decision tree where the first branch is avoiding one of these two pitfalls, and the second branch is the Markov process by which one chooses an EOQ cycle when inventory reaches zero. Figure 4 depicts this process.

Figure 4: The branching decision process. First, there is a choice of proceeding to Branch 1 and taking Non-EOQ action or Branch 2 and taking an EOQ action. This formulation depends upon whether the closing inventory of previous period is greater or less than 10.



(a) Decision process when the closing inventory of previous period is strictly less than ten.

(b) Decision process when the closing inventory of previous period is greater than ten.

We will formulate the probabilities of choosing Non-EOQ actions as simple Logit functions of time, habit formation and whether it is a High cognitive load treatment. As the experimental design prunes Branch 1 for the EOQ treatment for the most part, of key interest here is whether High cognitive load leads to larger probabilities of Non-EOQ actions. Then when an individual chooses an order once inventory reaches zero, we use a low rationality Markov model to specify how participants switch from one EOQ cycle length to another. In this model we examine the probability of switching to an at least as profitable EOQ action and the viscosity to making large changes to EOQ cycle length.

4.1 Branch Decision 1

To investigate the factors that influence the probability of participants deviating from an EOQ action in any one of the sixty decision rounds with financial incentives we first define and indicator function for

$$NonEOQ_{i,r} = \begin{cases} 1 & \text{if } q_{i,r} \text{ is not an EOQ action in decision round } r \text{, and} \\ 0 & \text{otherwise.} \end{cases}$$

where $r \in \{1, 2, \ldots, 60\}$.

We estimate sets of Logit regressions on the probability a participant chooses a Non-EOQ action for two cases; one when the previous month's closing inventory is strictly less than ten and one when it is at least ten. In both cases we consider the following specification

$$Pr(NonEOQ_{i,r} = 1) = F(\beta_0 + \beta_1 Year_r + \beta_2 Month_r + \beta_3 High + \beta_4 NonEOQACC_{i,r-1}).$$

Here F is the logistic cumulative distribution function and $NonEOQACC_{i,r-1}$ is the total number of rounds participant i has deviated from EOQ up through round $r-1$ - this is intended to capture any habit formation. Note this is a running count of an participant's Non-EOQ actions in either state.

The Logit regression results are presented in Table 7: Panel A for the case $I_{t-1} < 10$ and Panel B for the case $I_{t-1} \geq 10$. For the prior case, deviations from an EOQ action occur due to the possibilities of stockouts. While our design was motivated to only allow participants in the Unrestricted to make such Non-EOQ actions, it may also happen in the Zero Only treatment when a participant orders less than 10 when the closing inventory of previous period is 0. There are only 40 such observations out of 4500, but we do include these in the Panel A results.[13] For the latter case - the closing inventory of previous period is at least ten - the only possible deviation from an EOQ action is to order a strictly positive amount, which is not allowed in the Zero Only treatment group.

Table 7: Logit regression on the probability of deviating from an EOQ action

	Panel A: $I_{t-1} < 10$			Panel B: $I_{t-1} \geq 10$		
$NonEOQ_{i,r}$	(1)	(2)	(3)	(4)	(5)	(6)
$Year_r$	-0.498***	-0.500***	-0.690***	-0.308***	-0.309***	-0.608***
	(0.126)	(0.128)	(0.160)	(0.096)	(0.097)	(0.134)
$Month_r$	0.194***	0.194***	0.153***	-0.115***	-0.114***	-0.141***
	(0.047)	(0.047)	(0.054)	(0.027)	(0.027)	(0.029)
High		0.255	0.216		-0.404	-0.193
		(0.425)	(0.311)		(0.376)	(0.296)
$NonEOQACC_{i,r-1}$			0.288***			0.307***
			(0.039)			(0.040)
Constant	-3.379***	-3.507***	-3.175***	-1.754***	-1.573***	-1.311***
	(0.583)	(0.630)	(0.690)	(0.338)	(0.397)	(0.430)
N	3032	3032	2875	3286	3286	3286
χ^2	34.10***	36.06***	97.89***	22.66***	22.90***	75.76***
$Pr(NonEOQ_{i,r}) = 1$	0.034	0.034	0.037	0.035	0.035	0.030

Standard errors in parentheses adjusted for clusters in individuals
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First, note the large negative values of the estimated coefficients pushing the argument of the logistic CDF to its far left tail. Thus all estimated probabilities of Non-EOQ actions are small as indicated by the last row of the table which reports the estimated probability of a Non-EOQ action at the average level of the factors. Second, two significant factors, both statistically and economically, are the number of years and the accumulation of experience of choosing Non-EOQ actions. The large estimated coefficient indicates there is significant learning to choose EOQ actions across the five years. The positive estimated value of the coefficient of $NonEOQACC_{i,r-1}$ captures the individual differences in the epiphany of the EOQ logic. The estimated coefficients for Months are statistically significant, but have low magnitude in moving probabilities meaningfully are of opposite signs in two cases. This suggests that stockouts are more likely later in a year while ordering when there is excess inventory is less likely later in a year. Surprisingly there is no significant effect of having a high cognitive load on taking

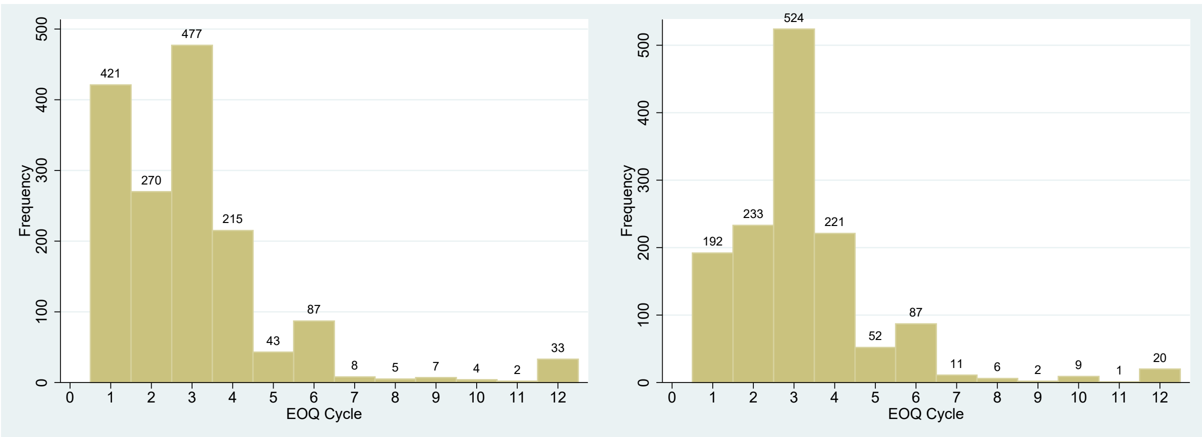
[13] Also there is another possible way to deviate from an EOQ action in the Zero Only treatment. Participants may have positive closing inventory of previous period that is less than 10 but are not allowed to place order (138 out 4500 observations). We exclude these observations as they are not by choice.

Non-EOQ actions. Thus the performance differences must come from the types of EOQ actions one takes under high cognitive load. Overall we interpret this evidence that providing the more complicated choice set does lead to some Non-EOQ actions, but these choices diminish with experience.

4.2 Branch Decision 2: A Markov model of EOQ cycle choice

Once an EOQ action is taken, the second branches in Figure 4, we consider how the participant chooses an EOQ cycle length. First, we make a slight modification to our definition of an EOQ cycle to handle situations in the Unrestricted treatment when the previous month's closing inventory is strictly positive but strictly less than ten. Let $\tilde{s}_{i,k}$ denotes the largest integer less than or equal to $\frac{I_{t-1}+q_t}{10}$. To see how this change of definition works consider the following simple example. If a participant has a closing inventory of 2 units from previous period and orders 8 units, then $\tilde{s}_{i,k} = 1$. Figure 14 shows histograms of EOQ cycles choices using this new definition in both Unrestricted and Zero Only treatments. This figure illustrates that we see more of the typically optimal EOQ cycles of length three in the Zero Only treatment, and more extreme EOQ cycles of lengths one and twelve in the Unrestricted treatment. Using the information of Figure 14 we move forward considering the set of possible EOQ cycle length $\tilde{s}_{i,k} \in \{1, 2, 3, 4, 5, 6, 12\}$.[14]

Figure 5: EOQ cycle choice histograms for Zero Only and Unrestricted treatments



(a) Unrestricted (n=1572) (b) Zero Only (n=1358)

Proceeding to the dynamics of a participant's sequence of EOQ cycle choices, we compare the relative ranking of alternative EOQ cycles by their monthly average profit conditional upon month. We denote this monthly average profit as $\bar{\pi}_t(\tilde{s}_{i,k})$. Notice that the pay off function depends upon t and will penalize relatively long EOQ cycles that generate excess inventory at the year's end. We report the values of $\bar{\pi}_t(\tilde{s}_{i,k})$ in Table 8.

We use this measure to evaluate whether a participant's EOQ cycle choice generates a higher

[14] Due to the low number of observations we round down EOQ cycles of $\tilde{s}_{i,k} = \{7, 8, 9, 10, 11\}$ to $\tilde{s}_{i,k} = 6$. Also, note that we are including $\tilde{s}_{i,k} = 5$ as an EOQ choice cycle given the high frequency it is chosen despite it not corresponding to a EOQ constant policy.

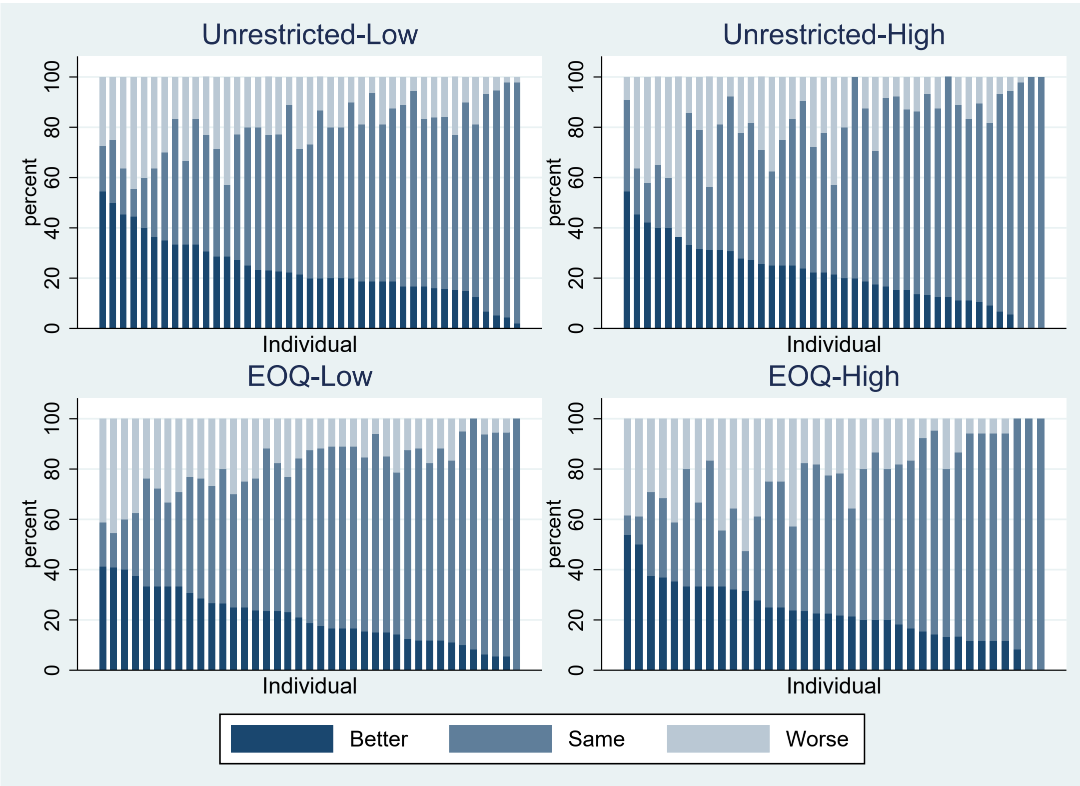
Table 8: Average monthly profit for alternative EOQ cycle choice given the current month

s	1	2	3	4	5	6	12[1]
Month 1-7	20	37.5	40	38.75	36	32.5	-
Month 8	20	37.5	40	38.75	36	26	-
Month 9	20	37.5	40	38.75	28.75	18.75	-
Month 10	20	37.5	40	30	20	10	-
Month 11	20	37.5	27.5	17.5	7.5	-2.5	-
Month 12	20	10	0	-10	-20	-30	-

[1] $\tilde{s}_{i,k} = 12$ always offers the lowest average monthly payoff

monthly average profit than their previous EOQ cycle choice. For each individual we consider the proportions of transitions to higher, the same, and lower profit cycles. We plot these proportions by treatment cell in Figure 6 and sort individuals by the proportion of 'better' transitions. This figure illustrates that participants exhibit rather limited individual rationality as their frequency of transitioning to a more profitable EOQ cycle tend to only slightly exceed that of switching to a less profitable cycle. Further there is a large amount of EOQ cycle choice repetition.

Figure 6: Proportions of Better, Same and Worse EOQ cycle transitions - ranked by Better



For a situation in which individuals similarly do not find the subset of higher ranked alternatives salient and there is an ordinal property - but not always monotonic in reward - to the set of alternatives, Shachat and Zhang (2017) introduced a Markov model of limited rationality to describe learning. We adapt that model for our setting. EOQ cycle transitions probabilities are governed by a two-stage process. In the first stage, probability is allocated between two subsets of possible EOQ cycles: NW, the subset of EOQ cycles no worse than $\tilde{s}_{i,k-1}$, and NB, the subset of EOQ cycles no better than $\tilde{s}_{i,k-1}$.[15] Specifically,

$$NW_t(\tilde{s}_{i,k-1}) = \{j \in \{1, 2, 3, 4, 5, 6, 12\} | \bar{\pi}_t(j) \geq \bar{\pi}_t(\tilde{s}_{i,k-1})\}$$

$$NB_t(\tilde{s}_{i,k-1}) = \{j \in \{1, 2, 3, 4, 5, 6, 12\} | \bar{\pi}_t(j) \leq \bar{\pi}_t(\tilde{s}_{i,k-1})\}$$

NW and NB may not be mutually exclusive; they will share the previous choice of an EOQ cycle when there are sufficient months remaining in the year. We assume that an α measure of probability is allocated to the NW set and a $1 - \alpha$ measure of probability is assigned to the NB set.

In the second stage, probability measure is allocated amongst the elements within each of these subsets. Such allocation is allowed to reflect participants possibly favouring the cycle having a smaller difference in length with the previous cycle. Specially, probability is allocated according to the number of steps between an element and the previous cycle length. The step count between EOQ cycle length j and j' is defined as,

$$\theta(j, j') = |j - j'| + 1.$$

A special case of $j = 12$ is treated as 2 steps from $j' = 6$.

We use the following weighting function to determine an EOQ cycle's assigned share of probability measure,

$$w(j|\tilde{s}_{i,k-1}, Z, \lambda) = \frac{\theta(j, \tilde{s}_{i,k-1})^\lambda}{\sum_{j' \in Z} \theta(j', \tilde{s}_{i,k-1})^\lambda}, \forall j \in Z$$

in which Z is either the NW or NB subset. In the proportional assignment, $\lambda \leq 0$ measures the strength of the bias for small changes within the subset Z. A decrease in λ corresponds to a growing bias. We calculate the transition probability for each EOQ cycle by adding up the probability measures it is allocated from the NW and NB subsets,

$$\begin{aligned} Pr(\tilde{s}_{i,k} = j|\tilde{s}_{i,k-1}) = \alpha \times \mathbb{1}_{(j \in NW_t(\tilde{s}_{i,k-1}))} \times w(j|\tilde{s}_{i,k-1}, NW_t(\tilde{s}_{i,k-1}), \lambda) \\ + (1 - \alpha) \times \mathbb{1}_{(j \in NB_t(\tilde{s}_{i,k-1}))} \times w(j|\tilde{s}_{i,k-1}, NB_t(\tilde{s}_{i,k-1}), \lambda) \end{aligned}$$

For example, if $\tilde{s}_{i,3} = 1$ and $\tilde{s}_{i,4} = 3$, the transition probability is $\alpha \frac{3^\lambda}{\sum_{j=1}^{6} j^\lambda}$, while if $\tilde{s}_{i,11} = 1$ and $\tilde{s}_{i,12} = 3$, the transition probability is $(1 - \alpha) \frac{3^\lambda}{\sum_{j=1}^{7} j^\lambda}$.

We estimate the two parameters of the Markov choice model for each treatment cell by maximum likelihood estimation and present them in Table 9. In all treatments, the magnitude of approximately 70% of α indicates that participants are more likely to move into their current NW set. However, the absence of the intervention and introducing cognitive load reduce the probability of switching to more profitable actions. The estimate of λ is larger in magnitude for the Unrestricted treatments, indicating a larger bias for small changes within the sets. The

[15] These subsets change depending on which month the choice occurs due to finite horizon. For instance, $\tilde{s}_{i,k} = 3$ would be in NW subset of $\tilde{s}_{i,k-1} = 1$ in month 10, but will change to be in NB subset in month 12. A detailed listing on NW and NB subsets for different month can be found in Appendix C.

ability to order in any month leads to a greater degree of action lock-in. However, the differences of the estimates of the parameters are not statistically significant when we estimate these coefficients jointly and test for differences due to heterogeneity.

Table 9: Parameter estimates for the Markov EOQ cycle choice model, standard errors in parentheses

Parameter	Unrestricted-Low	Unrestricted-High	Zero Only-Low	Zero Only-High
α	0.708 (0.041)	0.676 (0.040)	0.760 (0.031)	0.712 (0.032)
λ	-1.104 (0.217)	-1.320 (0.209)	-0.709 (0.178)	-0.782 (0.137)

Table 10: Differences in parameter estimates for the Markov EOQ cycle choice model

Parameter	α		λ	
Treatment Comparison	Difference	p-value	Difference	p-value
Unrestricted-Low vs Unrestricted-High	0.032	0.575	0.216	0.475
Zero Only-Low vs Zero Only-High	0.048	0.284	0.074	0.744
Unrestricted-Low vs Zero Only-Low	-0.052	0.310	-0.396	0.159
Unrestricted-High vs Zero Only-High	-0.036	0.487	-0.538	0.032

Overall we find the Unrestricted treatment leads to a small percentage of Non-EOQ actions, generating performance diminishing outcomes of excess inventories and stockouts. However, we find the likelihood of these events diminish over time and is surprisingly unaffected by high cognitive loads. The more complex choice sets of the Unrestricted treatment also leads to more inertia in EOQ cycle length choices inducing choice lock-in. This is a likely cause of participants choosing near rather than absolute optimal policies in the last two years. This is a similar phenomenon found in Caplin et al. (2011); as they increase choice set complexity participants tend to switch within a smaller range of values.[16] The effect of the High cognitive load is for participants to exhibit a lower level of rationality once they choose EOQ actions; their probability of choosing EOQ cycles that generate at least the same level of average monthly profit is lower than for those participants who do not have the competing PIN memorization task.

5 Conclusion

We present an experimental investigation to assess the effect of cognitive stress on inventory management decisions in an EOQ model. We exogenously impose cognitive stress from a PIN task that competes for the participants' short term memory resources, and reduce cognitive stress by introducing an intervention that limits the complexity of the inventory policy choice set. Increases in cognitive load negatively impact participants' performance. However, these negative impacts occur predominantly when participants first face the inventory decision problem. While

[16] See Caplin et al. (2011, page 2909) - Figure 4 for a comparison on the range of values observed with varying choice set complexity.

average performance is not statistically different, we note that only in the Zero Only-Low treatment cell do we observe the majority of participants eventually learn to use the optimal EOQ policy. We model and then estimate participants learning of monthly action choices using a Markovian learning framework. We find that the availability of the more complicated choice set causes some deviations from EOQ actions, but such deviations diminish with experience. Further, the ability to order in any month leads to a greater degree of EOQ cycle length choice lock-in. Increased cognitive load reduces the probability of switching to more profitable actions.

The EOQ is a prevalent tool of inventory managers in the field. Our results provide managerial insights, particularly in the case of inventory managers of multiple product lines. It is clear that asking such individuals to simultaneously complete multiple tasks impedes their learning of effective inventory management. Further, there is value in restricting the manager's possible actions to those consistent with EOQ policies. This suggests increasing the difficulty of overriding ERP recommendations will increase performance. Absent this intervention, there is a greater chance of locking into suboptimal EOQ cycles. Of course, in the long run we observe near identical performance with enough experience. But one should proceed with caution thinking that good management will arise eventually with experience; our environment is constant and certain. Chen and Wu (2017) demonstrated that changing ordering and holding costs will slow the learning process.

We believe this is a successful first step in evaluating and developing interventions to minimize the impact of cognitive stress on inventory management performance. Our *ex ante* expectation was that cognitive load would have the more severe impact that would manifest itself in more varied directions that choice set complexity. However, it does appear that presentation of policies has the more complicated, and hence providing more scope for intervention design, impact on the decision-making process. Some natural next steps are to explore how the choice set complexity and corresponding framing impact decision making in the other previously raised inventory management paradigms such as the newsvendor problem, (S, s) inventory management, and multi-tiered supply chains.

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A Experiment Instructions and Interface

Instructions for different treatments are presented as the texts/sentences in italics and square brackets below.

A.1 Instruction Page

Welcome

Welcome to today's experiment. Please read the following instructions carefully as they are directly relevant to how much money you will earn today. Please do not communicate with other people during the experiment. Please note that **you are not permitted to use pen and paper or a mobile phone**. Please kindly switch your mobile phone off or put it on silent mode. Students causing a disturbance will be asked to leave the room. You will enter all of your decisions in todays experiment using only the computer mouse. Please do not attempt to use the keyboard or remove the keyboard cover. The information displayed on your computer monitor is private and specific to you. All monetary amounts in todays experiment are expressed as experimental currency units (ECU). The conversion rate for ECU and GBP is 300 ECU = £1 cash payment. Your payment will be rounded up to the nearest ten pence.

If you have any questions at any point during today's session, please raise your hand and one of the monitors will come to help.

Task

In todays experiment, you will be making **inventory management decisions** for an enterprise called S-Store. S-Store sells coffee makers. You will perform this role for a sequence of 6 years. Every month you will decide how many coffee makers to order from the coffee maker supplier. Your earnings in this experiment will be proportional to the total profitability of S-Store. S-store will sell a new coffee maker model every year. Thus in the first month of a year your inventory always starts from zero. Further, any coffee makers remaining in inventory at the end of month 12 will be disposed of. To summarise, you will be making 12 monthly decisions for a year, and you will do this for 6 years in total.

You will have up to **4 minutes** to complete your task for each year. Year 1 is a practice round, and you will have up to 7 minutes to complete the task for this year. You should use this as an opportunity to familiarize yourself with the software and decision tasks. If you dont finish within the time allowed, the computer will automatically execute the remaining month(s) sales with the existing inventory. You will not be able to add inventory. A 'wait page' displays automatically if you spend less than the allowed time in a year. You will only be able to proceed to the next year when the remaining time runs out.

Before the decision making portion of the experiment begins, there will be a **Quiz** consisting of 7 simple questions to check your understanding of the task. Please answer the questions carefully. If you missed 3 or more questions, you would be asked review the correct answers before you can proceed to the task.

[The following italic texts are additional for treatments with High Cognitive Loads]

PIN

In addition to the task, you will be given a 7-digit PIN at the beginning of each year. The PIN is case sensitive, and consisting of numbers, uppercase and lowercase letters. You will have 15 seconds to remember the PIN. This is your KEY to unlock an account which contains an extra reward of 300 ECU. You can open the account at the end of each year by correctly entering the PIN. You will only have one attempt to correctly enter the pin to claim this extra reward.

Payment

Year 0 is a practice round, and you will receive no earnings from your decisions in this year. For **Years 1 through 5**, your earnings will accumulate across years. At the end of the experiment you will be paid £5 show-up fee and your accumulated earnings, converted to Pounds. Note, negative profit may occur if poor coffee maker ordering decisions are made. To ensure that no one will leave the experiment with a payment less than £5, a negative total profit made in Year 1 to Year 5 will be treated as 0 earnings.

A.2 Background Information

[The following Background Information section shows up on every decision page.]

Your Role:

S-Store is open 360 days per year. You are the inventory manager for S-Store. In your role, you will control S-Stores inventory level which determines the stores total profits.

We now explain how S-Stores, and correspondingly you, earns profit. While we are explaining how the calculations are made, during the decision tasks the computer will carry out these calculations and report the results to you.

S-Store sells coffee makers at a price of **7 ECU** per unit. S-Store can sell up to **10 coffee makers per month**. A coffee maker can only be sold if there is a unit held in inventory. If you hold 10 or more units in inventory at the start of the month, S-Store will sell 10 coffee makers that month. However, if there are less than 10 units held in inventory at the start of the month then S-Store will only sell that amount. For example, if there are 2 units held in inventory at the beginning of a month then S-Store only sells 2 units that month. *[(For Zero Only treatment only) You can only place an order when the current months opening inventory is 0. For example, if the current months opening inventory is 3 units, you cannot place an order this month, S-Store only sells 3 units this month.]* S-Stores sales revenue for a month is calculated as follows:

Sales revenue = 7 ECU * Number of units sold.

Your job is to manage the stores inventory levels by each month choosing an inventory order. Prior to the start of each month you can order coffee makers from the supplier to add to the inventory. Your inventory management determines the S-Stores total costs. S-Store pays two types of costs. One is the **ordering cost**. Every time you order a positive amount you have to pay an order cost. This ordering cost is **45 ECU**, and does not depend upon the size of the order. If you order zero coffee makers then you do not pay the 45 ECU ordering cost. Holding coffee makers in inventory is costly so S-Store pays a monthly **inventory holding cost**. S-Store pays monthly inventory holding cost is based on the average number of coffee makers held in inventory multiplied by the per unit monthly inventory holding cost of **1 ECU**. This is calculated as follows:

Inventory holding costs = 1 ECU * (Opening inventory + Order Quantity + Closing inventory)/2.

Calculation of S-Stores profits

Profits = Sales revenue - Ordering costs - Inventory holding costs

Your monthly earnings are equal to S-Stores monthly profits.

Examples:

1. Alices closing inventory of last month is 20 units, she placed an order of 0 units in this month.
   The demand for each month is 10 units.
   She made sales of 10 units.
   Her closing inventory of this month is $20 - 10 = 10$ units.
   Her profit in this month is equal to: $7 * 10 - 0 - 1 * (20 + 0 + 10)/2 = 55$.
2. Alices closing inventory of last month is 4 units, she placed an order of 5 units in this month.
   The demand for each month is 10 units.
   She only made sales of 9 units. Her closing inventory of this month is 0 units. Her profit in this month is equal to: $7 * 9 - 45 - 1 * (4 + 5 + 0)/2 = 13.5$.

A.3 Multiple Choice Questions prior to Decision Task

There are a couple of questions for you before the task, please use the information:

The demand for each month is 10 units.
Price of each coffee maker is 7.
Ordering cost is 45 per order.
Monthly inventory holding cost is 1 per unit.

Question 1 of 7
If the inventory level was 5 and you ordered 0 units. How many units will you SELL this month?

A 0
B 5
C 10
D 15

Question 2 of 7
If the inventory level was 0 and you ordered 15 units. How many units will you SELL this month?

A 0
B 5
C 10
D 15

Question 3 of 7
If you made sales of 10 units. What will be your SALES REVENUE this month?

A 0
B 10
C 25
D 70

Question 4 of 7
If you ordered 0 units. What will be your ORDERING COST this month?

A 0
B 1
C 45
D 70

Question 5 of 7
If you ordered 1 unit. What will be your ORDERING COST this month?

A 0
B 1
C 45

D 70

Question 6 of 7

If the inventory level was 0 and you ordered 10 units. You made sales of 10 units. What will be your HOLDING COST this month?

A 0
B 1
C 5
D 10

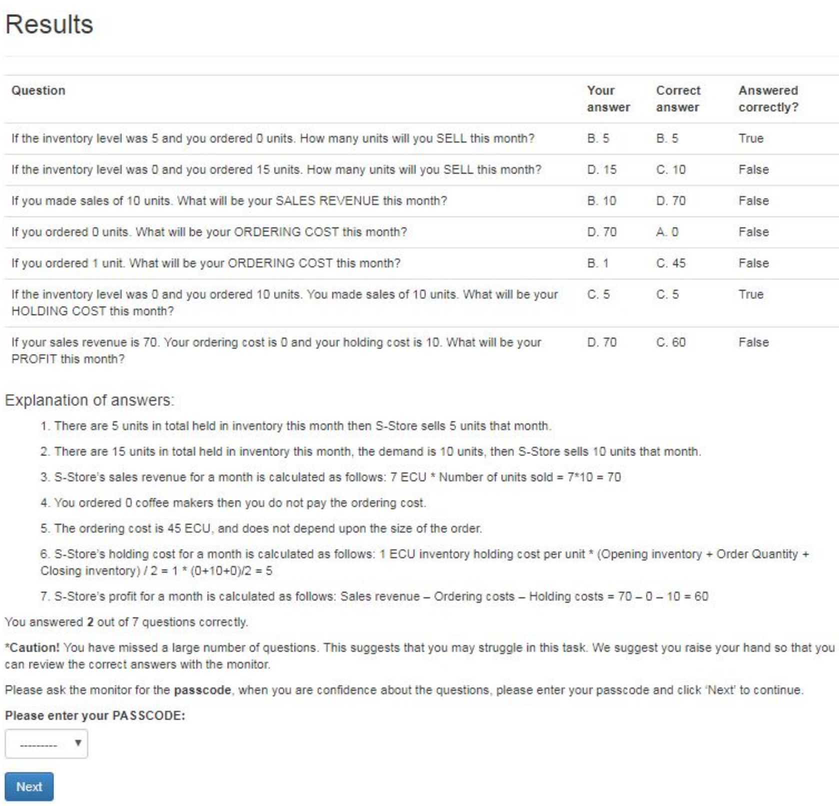
Question 7 of 7

If your sales revenue is 70. Your ordering cost is 0 and your holding cost is 10. What will be your PROFIT this month?

A 15
B 25
C 60
D 70

Figure 7 shows the result page of the multiple choice questions when participants had given more than 2 incorrect answers. Under such circumstances, they had to raise their hands to go through incorrectly answered questions with a monitor in order to obtain a passcode to proceed to the decision tasks.

Figure 7: Result Page of the Multiple Choice Questions



Results

Question	Your answer	Correct answer	Answered correctly?
If the inventory level was 5 and you ordered 0 units. How many units will you SELL this month?	B. 5	B. 5	True
If the inventory level was 0 and you ordered 15 units. How many units will you SELL this month?	D. 15	C. 10	False
If you made sales of 10 units. What will be your SALES REVENUE this month?	B. 10	D. 70	False
If you ordered 0 units. What will be your ORDERING COST this month?	D. 70	A. 0	False
If you ordered 1 unit. What will be your ORDERING COST this month?	B. 1	C. 45	False
If the inventory level was 0 and you ordered 10 units. You made sales of 10 units. What will be your HOLDING COST this month?	C. 5	C. 5	True
If your sales revenue is 70. Your ordering cost is 0 and your holding cost is 10. What will be your PROFIT this month?	D. 70	C. 60	False

Explanation of answers:

1. There are 5 units in total held in inventory this month then S-Store sells 5 units that month.
2. There are 15 units in total held in inventory this month, the demand is 10 units, then S-Store sells 10 units that month.
3. S-Store's sales revenue for a month is calculated as follows: 7 ECU * Number of units sold = 7*10 = 70
4. You ordered 0 coffee makers then you do not pay the ordering cost.
5. The ordering cost is 45 ECU, and does not depend upon the size of the order.
6. S-Store's holding cost for a month is calculated as follows: 1 ECU inventory holding cost per unit * (Opening inventory + Order Quantity + Closing inventory) / 2 = 1 * (0+10+0)/2 = 5
7. S-Store's profit for a month is calculated as follows: Sales revenue – Ordering costs – Holding costs = 70 – 0 – 10 = 60

You answered **2** out of 7 questions correctly.

*__Caution!__ You have missed a large number of questions. This suggests that you may struggle in this task. We suggest you raise your hand so that you can review the correct answers with the monitor.

Please ask the monitor for the **passcode**, when you are confidence about the questions, please enter your passcode and click 'Next' to continue.

Please enter your PASSCODE:

Next

A.4 Decision Tasks

Prior to each year's decision tasks, a mini-instruction page appears. Figure 8 is an example with PIN task. For treatments with high cognitive loads, the pin page follows (Figure 9).

An example of the ordering decision page is shown in Figure 10. Participants move the slider

Figure 8: An example of Instruction Page with PIN task

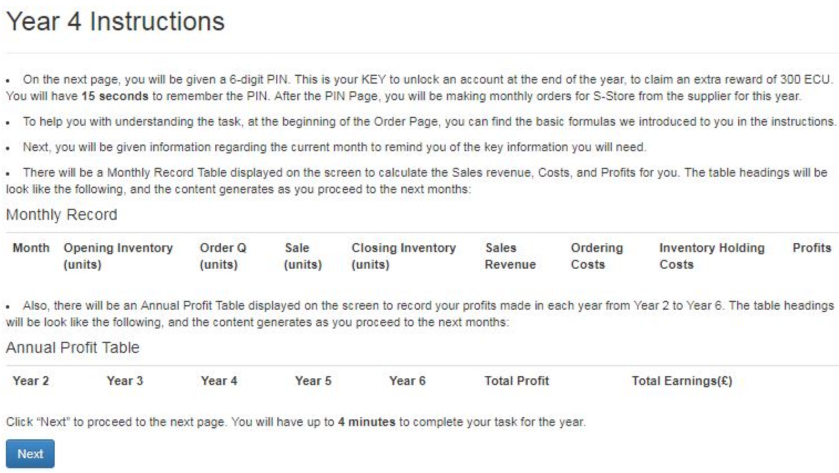
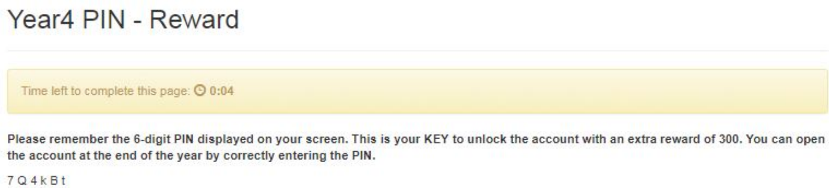


Figure 9: PIN Page prior to Ordering Page



to enter their decision of order quantity for each month. Order quantities, costs, and profits of previous months are also displayed on the page. If participants completed the year's decision task within 4 minutes, they had to wait until the end of 4 minutes.

They were then prompted to enter the PIN (Figure 11), followed by the end of the year result page (Figure 12).

B Post-Experimental Survey, Demographics and Summary Statistics of Participants

Participants were asked to fill a simple questionnaire at the end of the experiment for us to collect some demographic information.

The following are some summary statistics of the participants.

Table 11: Demographics in Participants

Age (mean)	25.6
Gender (% female)	65%
Education (%Undergraduate)	51%

One can observe that 37% of the participants are from Social Science & Management, among which they may have training in operations management or have been exposed to the EOQ model before.

Figure 10: Ordering Page

You are making inventory orders for Year 4

Time left to complete this year:2 minutes 58 seconds

Basic Formula:

Profits = Sales revenue - Ordering costs - Inventory holding costs

Sales revenue = 7 ECU * Number of units sold

Ordering costs = 0 or 45

Inventory holding costs = 1 ECU inventory holding cost per unit * (Opening inventory + Order Quantity + Closing inventory) / 2

Period Information:

- This is Month **7** of the 12 months in Year 4.
- The demand for each month is 10 units.
- Price of each coffee maker is 7.
- Ordering cost is 45 per order.
- Monthly inventory holding cost is 1 per unit.

Monthly Record

Month	Opening Inventory (units)	Order Q (units)	Sale (units)	Closing Inventory (units)	Sales Revenue	Ordering Costs	Inventory Holding Costs	Profits
1	0	41	10	31	70.00	-45.00	-36.00	-11.00
2	31	0	10	21	70.00	0.00	-26.00	44.00
3	21	0	10	11	70.00	0.00	-16.00	54.00
4	11	0	10	1	70.00	0.00	-6.00	64.00
5	1	74	10	65	70.00	-45.00	-70.00	-45.00
6	65	0	10	55	70.00	0.00	-60.00	10.00

Your **Opening Inventory** of this month is **55** units.

How many units (coffee makers) would you like to order for this month?

100

(Please move the slider to select the number of coffee makers you would like to order from the supplier this month. The slider starts from a random point every month. Choose 0 if you do not wish to make an order for this month.)

Next

Annual Profit Table

Year 2	Year 3	Year 4	Year 5	Year 6	Total Profit	Total Earnings(£)
-134.00	254.00				254.00	0.85

Figure 11: Enter the PIN Page

Year4 PIN - Reward

Please enter the combination of your KEY to open the reward of 300.

PIN1 :

C

PIN2 :

6

PIN3 :

m

PIN4 :

PIN5 :

PIN6 :

Next

Figure 12: End of the Year Result Page

Year 4 Result

You guess **C6mGEB**, the PIN was **7Q4kBt**. PIN wrong. You won 0.

Month	Opening Inventory (units)	Order Q (units)	Sale (units)	Closing Inventory (units)	Sales Revenue	Ordering Costs	Inventory Holding Costs	Profits
1	0	41	10	31	70.00	-45.00	-36.00	-11.00
2	31	0	10	21	70.00	0.00	-26.00	44.00
3	21	0	10	11	70.00	0.00	-16.00	54.00
4	11	0	10	1	70.00	0.00	-6.00	64.00
5	1	74	10	65	70.00	-45.00	-70.00	-45.00
6	65	0	10	55	70.00	0.00	-60.00	10.00
7	55	0	10	45	70.00	0.00	-50.00	20.00
8	45	0	10	35	70.00	0.00	-40.00	30.00
9	35	0	10	25	70.00	0.00	-30.00	40.00
10	25	0	10	15	70.00	0.00	-20.00	50.00
11	15	0	10	5	70.00	0.00	-10.00	60.00
12	5	0	5	0	35.00	0.00	-2.50	32.50
PIN WRONG								+ 0
Total:								348.50

Annual Profit Table

Year 2	Year 3	Year 4	Year 5	Year 6	Total Profit	Total Earnings(£)
-134.00	254.00	348.50			602.50	2.01

Next

Figure 13: Post-Experimental Survey

Questionnaire

Please answer the following questions.

1. What is your age?

----

2. What is your gender?

- Male
- Female

3. What is your country of citizenship?

United Kingdom

4. Please indicate your current level of education :

- Undergraduate
- Postgraguate

5. Please select your subject area :

----

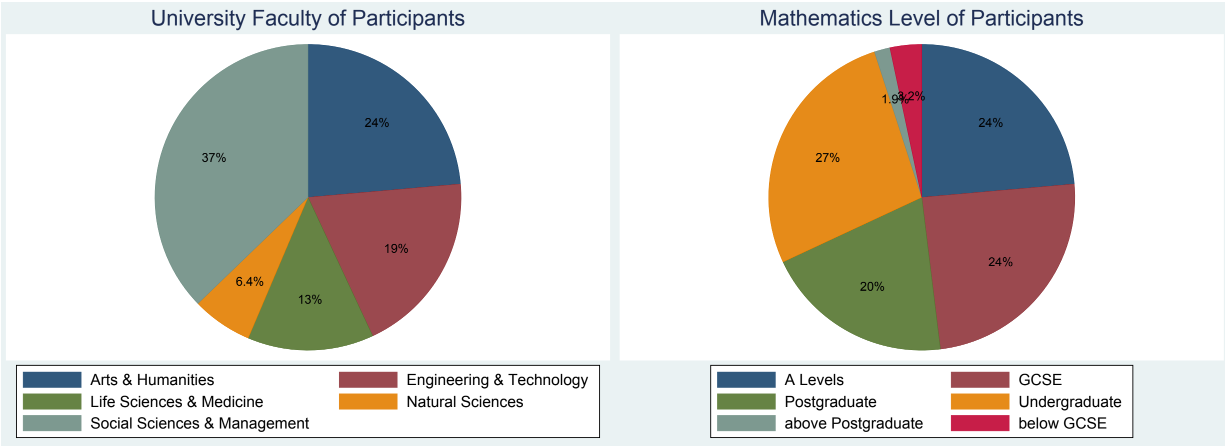
6. How would you describe you mathematical skill level?

----

7. On a scale of 1-5, how strongly were you motivated by the PIN and the bonus? (1 - I only cared about the PIN; 3- I cared about the PIN and the inventory decision task equally; 5 – I cared about the inventory decision task only and disregarded the PIN) :

Next

Figure 14: Distribution of University Programs Participants study and Mathematics levels of participants (self reported)



(a) Distribution of University Programs Participants study

(b) Mathematics levels of participants

Table 12: Regression on PIN and demographic information

	(1) Annual Profit	(2) Annual Profit
Year 1	-129.08***	-130.78***
	(19.30)	(18.84)
Year 2	-71.18***	-70.65***
	(16.84)	(16.90)
Year 3	-31.00**	-30.90**
	(13.76)	(13.23)
Year 4	-13.95	-13.74
	(12.28)	(11.89)
Unrestricted	-22.32**	-33.26***
	(11.22)	(12.56)
High·Correct PIN	27.26*	19.09
	(15.96)	(16.13)
Age		-2.42***
		(0.78)
Male		16.14
		(11.88)
Postgrad		-7.44
		(12.40)
STEM		8.66
		(13.73)
Math level		-5.98
		(5.20)
Constant	417.18***	505.75***
	(15.61)	(33.00)
N	385	385
R^2	0.18	0.22

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Possible NW NB sets by month

Table 13: The No worse than and No better than sets for each EOQ cycle by month

Months 2-8	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{1, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4\}$	$NB = \{1, 2, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{3, 4\}$	$NB = \{1, 2, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{2, 3, 4, 5, 6\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 9	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{1, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3, 4\}$	$NB = \{1, 2, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{3, 4\}$	$NB = \{1, 2, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 10	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2, 3\}$	$NB = \{1, 2, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{3\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{2, 3, 4\}$	$NB = \{1, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{1, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 11	$\tilde{s}_{i,k-1} = 1$	$NW = \{1, 2, 3\}$	$NB = \{1, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{2\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{2, 3\}$	$NB = \{1, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{1, 2, 3, 4\}$	$NB = \{4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$
Month 12	$\tilde{s}_{i,k-1} = 1$	$NW = \{1\}$	$NB = \{1, 2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 2$	$NW = \{1, 2\}$	$NB = \{2, 3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 3$	$NW = \{1, 2, 3\}$	$NB = \{3, 4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 4$	$NW = \{1, 2, 3, 4\}$	$NB = \{4, 5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 5$	$NW = \{1, 2, 3, 4, 5\}$	$NB = \{5, 6, 12\}$
	$\tilde{s}_{i,k-1} = 6$	$NW = \{1, 2, 3, 4, 5, 6\}$	$NB = \{6, 12\}$
	$\tilde{s}_{i,k-1} = 12$	$NW = \{1, 2, 3, 4, 5, 6, 12\}$	$NB = \{12\}$